# Human Infrastructure & Human Activity Detection

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***Abstract: Prior to committing personnel to investigate a building or suspicious site such as a cave, it is imperative to determine the importance and current danger of the site. To this end, sensors on a robotic platform can interrogate the site prior to sending in personnel. This paper investigates methods to exploit multiple sensor modalities in order to automatically 1) detect human presence, and 2) detect human infrastructure and recent human activity. The paper describes 10 experimental scenarios to support these two tasks, demonstrates what type of inference each modality can make, and shows how to fuse the information from all sensors. Experimental results are also provided for the detection of the presence of humans.***

**Keywords:** Sensor fusion, Spatial-temporal processing, human infrastructure, human activity.

## 1 Introduction

During security sweeps, it is essential that the scout is able to determine whether or not a building is occupied, and whether an unoccupied building has accommodated recent human activity or is simply abandoned. Such situational awareness is essential for scouts to safely enter buildings relevant to their mission. Similarly, scouts may need to gather intelligence, surveillance and reconnaissance (ISR) information about tactically important sites such as caves, tunnels, and other hard to reach locations. The scout must understand if it actually includes human infrastructure such as electrical wiring, man-made vents, presence of electrical utilities, generators, cooking utensils, etc. If the site does support human activity, the scout then must know if the site is presently occupied, recently used, or abandoned.

The ability for the scout to obtain information about human presence or recent human activity via the use of mobile sensors would be most advantageous. This paper discusses possible multi-sensor solutions for the automatic detection of human presence and recent human activity. The technology to detect the presence of humans is much more mature than the technology to detect recent human activity after the people have vacated the area. For instance, researchers are developing sensors systems that detect footfalls (or gait) [1, 2], speech, the spectral response of human skin, etc [3]. Little work has focused on the detection of human infrastructure in remote sites and the indirect detection human activities. Fortunately, when people perform activities, they leave behind many clues that can be exploited by forensic sensor systems. For instance, if the people used any machinery, the machine could still be warm. It is possible that the concentration levels of human pheromones in a room may reveal the prior presence of people.

This paper is organized as follows. Section 2 lists the different modalities that are being considered, and Section 3 lists different data collection scenarios that have been executed to test multi-sensor human presence and/or human activity detection. Section 4 details a fusion experiment for the detection of human presence, and Section 5 discusses a proposed approach for human infrastructure and activity detection. Finally, Section 6 concludes the paper and discusses further research.

## 2 Sensors

In order to detect human infrastructure and activity, several common sensor modalities are considered. Because mission requirements change, these sensors cannot be deployed at fixed locations. Rather, they must fit on a mobile platform so they can travel inside the building or other tactical sites. As a result, the form-factor of the sensors must be small enough to fit on a robotic platform. Figure 1 shows a model of a prototype robotic system that includes the requisite suite of sensors[1]. Sensors that can meet the detection functionality and size requirements are listed below. Figure 2 provides pictures of many of these sensors and the descriptions of these sensors are given below.

- **Acoustic** sensors used are the piezo electric microphones and can be used to detect speech, sounds generated by machinery, etc.
- **Seismic** sensors are 3-axis sensors that can detect the vibrations in the ground. They are used to detect footfalls, vibrations caused by machines being operated,

[1] The actual robotic prototype will be available before publication of the final version of this paper.

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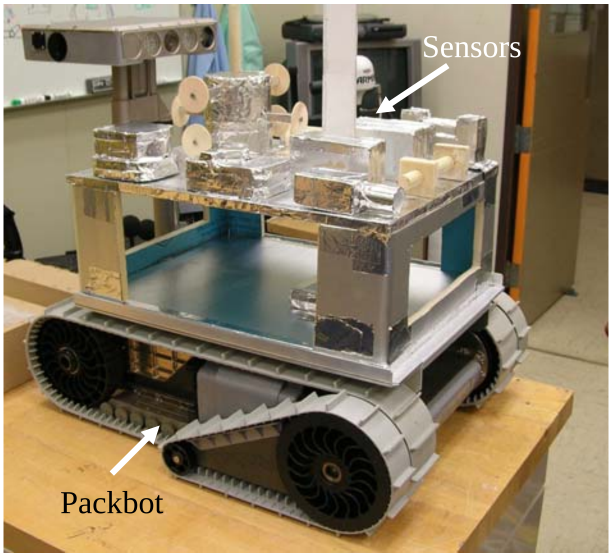


Figure 1: Mobile platform (Packbot) with mockup model of senor packages.

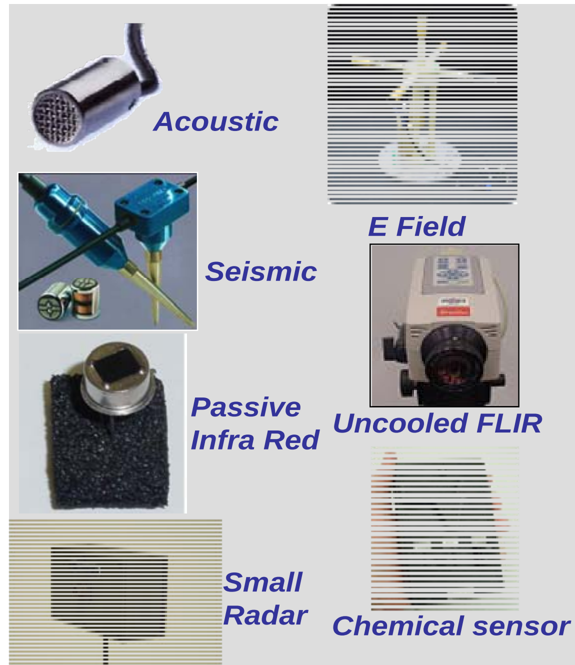


Figure 2: Acoustic (piezo electric microphone), Seismic (accelerometer), Passive Infrared (motion detector), small Radar (2.5W, 5.8 GHz Radar), E-Field (Quasar 3-axis), Forward looking infrared camera, 10 compound chemical sensors for human activity detection.

etc. Accelerometers can also detect vibrations in pipes that are produced by the flow of water.

- **RF** detectors can detect any RF activity such as the use of cell phones.
- **Magnetic (B-field)** sensors can be used to detect ferromagnetic materials carried by people, e.g., keys, firearms, and knives. These sensors may also detect the usage of computer monitors.
- **Electrostatic (E-field)** sensors can be used to detect the built-up electric charge on personnel. Together with magnetic sensors, they can also detect electrical activity in the vicinity such as the usage of computer keyboards.
- **Chemical** sensors can be used to detect the presence of different kinds of chemicals in the atmosphere such as pheromones and household chemical vapors.
- **Passive infrared** devices are very inexpensive sensors that detect the nearby presence of a warm body, e.g., a human, within a cone shaped field of view.
- **Visible imagers** can capture color or grayscale video for human gait detection and object recognition.
- **Infrared imagers** can detect and localize hot bodies and warm surfaces, including the vents in tunnels. They can also provide thermal profiling of buildings, where warmer rooms are indicative of current or recent human inhabitation.
- **Micro Radar**s can detect and track people in short ranges. Low frequency radars can even see through walls.

## 3 Data Collections

Multi-sensor data was collected for a number of different scenarios. Most of the data collection occurred in a remote building that contains some machinery. For most scenarios the following sensors collected data: visible camera, infrared camera, magnetic, electrostatic, acoustic, seismic, and chemical. Some scenarios were designed to evaluate multi-sensor systems for detection of human presence, and the other scenarios were designed for sensing prior human activity.

The scenarios to evaluate direct human presence detection include:

- **Corridor Scenario:** The suite of sensors is placed at the center of a hallway. A persons walks down the hallway. The goal is to determine the range from the sensors at which the person is detected.
- **Human Walking and Talking Scenario:** The sensors are observing people walking and talking in a room. The goal is to determine how many modalities can detect the standard human activities.

Other experiments are designed to indirectly detect humans by detecting signals that humans create while using machinery. These scenarios include:

- **Cell Phone Scenario:** Sensors are observing the ringing and usage of a cell. Cell phones are very prevalent nowadays, especially in the third world countries where the wired-telephone infrastructure is rather limited. The goal is to detect their usage using multiple modalities, such as RF detectors and acoustic sensors.

- **Bathroom Scenario**: A person flushes a toilet, and sensors are located in-situ and remotely to detect the flushing event. The goal is to determine which sensors can remotely detect the water flow through the pipes as a result of the flushing event. For instance, an accelerometer attached to the pipes far away from the bathroom should detect the event. Also, the opening of the bathroom door can be detected by magnetic, seismic, electrostatic, and both IR and visible cameras.
- **Computer Keyboard Scenario:** The goal is to detect the usage of the keypad using several sensor modalities. In this information age, computer keypads are used for a very large number of applications including planning, information downloads, communications, etc.
- **Computer Monitor Scenario:** The sensors are observing the usage of a computer monitor: The goal is similar to that of the keypad usage.

The final class of scenarios is used to determine the feasibility of sensors to determine either current or prior human activities. Sensors, for example, could detect signals radiating from residual materials and energy directly due to human activity or due to human infrastructure to support the activity. The scenarios include:

- **Machine Shop Scenario:** Sensors observed a drill press in a secluded building. The press was used to drill a bore in a wooden plank. The goal here is to find how many sensor modalities can detect the machine while in-use and determine how long after the machine is turned off that the residual information can signify prior usage.
- **Conference Room Scenario:** In this scenario, people sat around a table and talked to each other. Some of them were smoking cigars and some were drinking coffee. After a period of time, they left the conference room, leaving behind burning cigars and unfinished coffee. The sensors observe the room after the people leave. The goal for the sensor is to determine that the conference room was recently used by some people due to the warm seats and chemical scents left behind. It is also important to determine how long the sensors can continue to detect prior human presence.
- **Vent Scenario:** A cave or tunnel that is currently supporting human activities will require vents to circulate in fresh air. The goal of this scenario is to determine which modalities can distinguish man-made air circulation from natural air movement, e.g., wind.
- **Portable Generator Scenario:** In a cave or a tunnel, it is most likely that a portable generator will be used. The goal is to detect this man-made object, both while it is being used and a few hours after its operation.

# 4 Detection of Human Presence

The detection of personnel may be accomplished either by directly detecting the person or by indirectly detecting the actions or objects associated to a human being. Direct means of detecting personnel include the usage of chemical, electrostatic, passive infrared (PIR), and imagers (visible and infrared). For instance, the chemical sensor is used to detect human pheromone by producing appropriate sensing outputs. Algorithm development for the chemical sensor is still in progress. Electrostatic sensors detect changes to the ambient electric field caused by static charges on the human skin. The output of the electrostatic sensor produces a detectable signal when a person is walking near the sensor (see Figure 3), and a simple threshold detector can detect the presence of a body. The PIR generates an output that is proportional to the body temperature of a person. A simple threshold

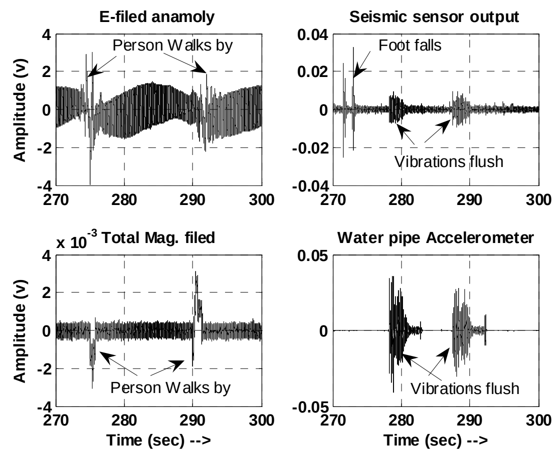


Figure 3: Different sensor outputs in Bathroom scenario

above the ambient noise would detect the presence of a hot body within the vicinity of the PIR sensor. Imagers can distinguish the silhouette of the human being when there is sufficient contrast from the background. Furthermore, it can be possible to segment human skin from an image based upon color [4]. Finally, when the human walks, the change of the human's silhouette due to his/her gait produces a unique signature [13]. Indirect means of detecting personnel include the usage of acoustic, seismic, magnetic, passive infrared (PIR), and chemical information collected through the respective sensors. Acoustic sensors can capture human speech, and one can exploit speech processing algorithms to determine whether or not human speech can be extracted from the background noise. In order to detect the presence of people, the acoustic signal spectrum between 50 Hz to 2000 Hz is analyzed. An algorithm [1] has been developed to detect personnel based the statistical analysis of the energy content in at least three of the four bands, where each band is roughly 500 Hz. A seismic sensor detects the closing of the door, if it is slammed against the frame. It also detects the footfalls of a walking person.

We have developed an algorithm to detect the gait frequency of humans [1, 2] using seismic sensor data. The typical gait frequency lies between 1.8 to 2.2 Hz. If these frequency components and their harmonics are present in the seismic data, then it is likely that there is a person present in the neighborhood of the sensor. Figure 4 shows the output of a seismic sensor. In the figure, the signature of the footsteps appears as a spike that repeats at a characteristic frequency. A magnetic sensor detects the opening and closing of a door through the changes in magnetic flux. If a person carries any ferromagnetic material, such as keys or short-guns, the magnetic sensor also generates an output that can be threshold to detect the presence of such a material. An algorithm for tracking the movement of ferromagnetic material [5] can be used as an indirect indication of the presence of a person.

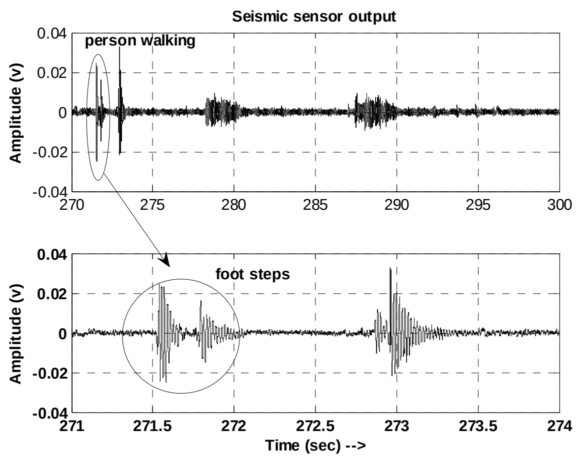


Figure 4: Foot falls identified in the seismic sensor output

The remainder of this section demonstrates the fusion of acoustic, PIR, and seismic sensors for the direct detection of humans walking through a hallway. The whole fusion system is evaluated over data collected in support of the Corridor Scenario. It consists of determining the likelihood of human presence via the signal level of each sensor, and then, combining these likelihoods via Bayesian fusion to obtain the posterior probability of human presence given the signal levels of all three sensors.

Figure 5 shows the output of the signal levels of the three sensors, and Figure 6 shows the ground truth location of the person in the hall. The hall is x meters long so that a location of 0 and X means that the person is located at one end of the hall or the other. The sensors are located at Y, which is near the center of the hallway. The person is walking over the interval between 70 and 130 seconds. The acoustic and seismic signals indicate footfall signatures when the person is passing close to the sensors. Furthermore, the PIR sensor provides a bipolar response when the person passes within the field of view. The seismic signal also includes significant background noise.

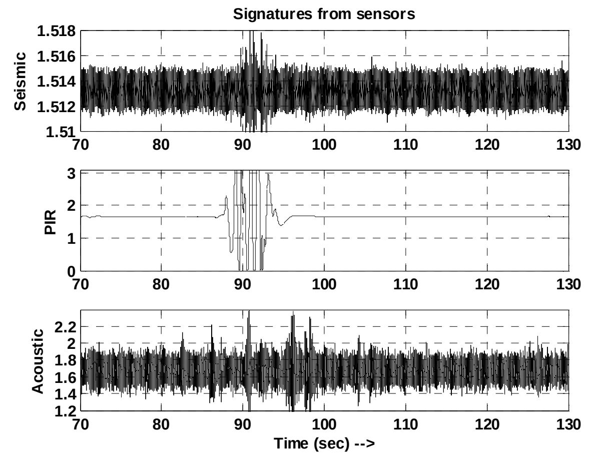


Figure 5: Output of Acoustic, PIR and Seismic Sensors


Figure 6: Corridor experiment – Ground truth

To detect people, the acoustic and seismic data is processed to form spectral and gait features, respectively, as described in [1]. For the PIR data, the signal magnitude forms the features. Next, the distribution of the features conditioned on the different hypotheses is determined. Specifically, we define $H_0$ and $H_1$ as the null and human present hypotheses. The likelihood of each hypothesis is defined as the probability of the observation, i.e., feature, conditioned on the hypothesis,

$$l_{H_i}(x_s) = p(x_s \mid H_i) \tag{1}$$

for $i$ =1,2 and $s \in \mathcal{S}$, where $\mathcal{S}$ ={acoustic, PIR, seismic}. The conditional probability is modeled as a Gaussian distribution,

$$p(x_s \mid H_i) = \mathcal{N}(x_s; \mu_{s,i}, \sigma^2_{s,i}). \tag{2}$$

The statistics of the distribution of the signal data for a given hypothesis is determined by using the sample mean and variance of training data. Let $x_{s,j}$ represent the time series associated to the $s$ sensor. Then,

$$\mu_{si}^2 = \frac{1}{|\mathcal{H}_i|} \sum_{j \in \mathcal{H}_i} x_{s,j}, \quad (3)$$

$$\sigma_{s,i}^2 = \frac{1}{|\mathcal{H}_i|} \sum_{j \in \mathcal{H}_i} (x_{s,j} - \mu_{s,j})^2, \quad (4)$$

where $\mathcal{H}_0$ and $\mathcal{H}_1$ represent the time indices that a person is absent and present in the time series, respectively.

Now, (1) – (2) can be used to determine the posterior probability of human presence given a single sensor observation. Namely,

$$p(H_1 | x_s) = \frac{l_{H_1}(x_s) p(H_1)}{l_{H_0}(x_s) p(H_0) + l_{H_1}(x_s) p(H_1)}, \quad (5)$$

where $p(H_0)$ and $p(H_1)$ represent the prior probabilities for the absence and presence of a human, respectively. This paper assumes an uninformative prior, i.e., $p(H_0)=p(H_1)=0.5$. Figure 7 shows the posterior probabilities of the three sensors as function of time for the corresponding signal data in Figure 5. The closest point of approach of human to the sensor package occurs at t = 90 sec, which corresponds to the case where the posterior probability approaches 1 in figure 7.

The fusion of the sensors can easily be implemented via Bayes rule by making the reasonable assumption that the sensor data for different modalities are statistically independent when conditioned on one of the two hypotheses. The posterior probability of human presence given data from all three sensors is,

$$p(H_1 | \mathbf{x}) = \frac{p(H_1) \prod_{s \in \mathcal{S}} l_{H_1}(x_s)}{p(H_0) \prod_{s \in \mathcal{S}} l_{H_0}(x_s) + p(H_1) \prod_{s \in \mathcal{S}} l_{H_1}(x_s)}, \quad (6)$$

where $\mathbf{x} = [x_{\text{acoustic}}, x_{\text{PIR}}, x_{\text{seismic}}]^T$ is the concatenation of features from all three sensor modalities. Figure 7 also shows the posterior probability that is the result of the data fusion. In the end, a detector is simple declaring a human if the posterior exceed a threshold. Clearly, the PIR is the best single sensor for detecting personnel. The fusion is able to maintain a high posterior probability when the PIR is able to detect the human. One downside to the PIR is its limited field of view. Fortunately, the fusion given by (6) provides the advantage of detecting a human when the human fails to cross through the field of view of the PIR.

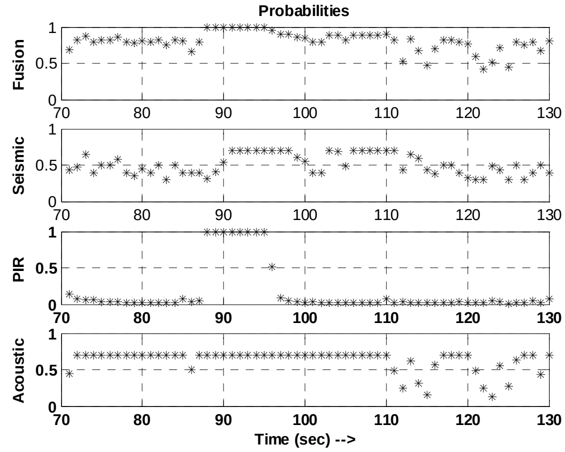


Figure 7: Posterior probabilities of Acoustic, PIR, and Seismic sensors and after Fusion

The performance of this detection system can be enhanced by considering the temporal signature of the target due to footfalls. Furthermore, imagers can be used to collect a feature based upon gait. Future work will investigate the performance gains by using better features.

# 5 Detection of Human Activity and Infrastructure

This section discusses human activity and infrastructure detection. A number of scenarios described in Section 3 are applicable. This section will focus on the Machine Shop scenario to illustrate how sensor data can be used to distinguish patterns caused by human activities from those caused by natural phenomena. The scenario covers all aspects of the human activity and infrastructure detection that we would like to address.

The Machine Shop scenario consists of data collected from sensors observing a secluded room that includes a drill press. A color video camera and a long-wave infrared (LWIR) camera were aimed at the drill press from a distance of 20 feet with similar field-of-views. An acoustic sensor (microphone), a chemical sensor, a seismic sensor, a magnetic sensor, and an electrostatic sensor were placed within 10 feet of the drill press. An identical suite of sensors was placed outside the room. An electrostatic sensor was placed near an electrical power distribution box that is far away from the room. During the operation of the drill press, the door to the room was closed. Prior to the actual experiment, all sensors were allowed to collect background noise for about 3 minutes. Then an operator opened the door, went into the secluded room, closed the door, and walked to the drill press, and turned on the drill press. After that, the operator drilled a wooden plank for about 3 minutes and then left the room. The infrared camera was on for another three hours after the drill press was turned off. Some of the sensors used in this experiment are shown in Figure 2.

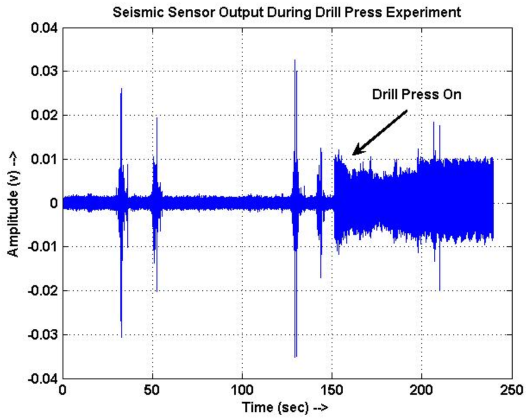


Figure 8: Seismic sensor output when the drill press is turned on during the machine shop experiment.

The ultimate goal is to design a robotic sensor system that can roam a site and automatically determine that the site contains man-made equipment, i.e., human infrastructure, which currently support (or recently supported) human activity. To this end, the sensors must monitor the site and determine if the output signals are consistent with the usage of man-made machinery as opposed to a benign background.

Various sensors can be used to detect infrastructure. In the Machine Shop scenario, magnetic and electrostatic sensors can easily detect when the drill press is active. Successful monitoring is accomplished by considering the sensor outputs from different locations, including the sensor suites near the drill press and outside of the secluded room, as well as those away from the room at the electrical distribution box of the building.

Figure 9 shows the magnetic and electrostatic sensor outputs before and during when the drill press is turned on. When the drill press is off, the ambient E and B fields include a dominant 60Hz harmonic due to radiation from outside power lines. Furthermore, the 60Hz E and B field harmonics are 90 degrees out of phase. Because the power lines are not in the vicinity, the 60Hz signal is noisy. When the drill press is on, the higher resulting signal amplitudes and the fact that the phase shift between the E and B fields are no longer 90 degrees offer clues that some sort of man-made machine is currently operating.

Visible cameras provide good clues about the presence of the man-made object. Pattern recognition technology may some day allow for the automatic detection and recognition of different machines for imagery collected by visible cameras. For the near term, automatic techniques

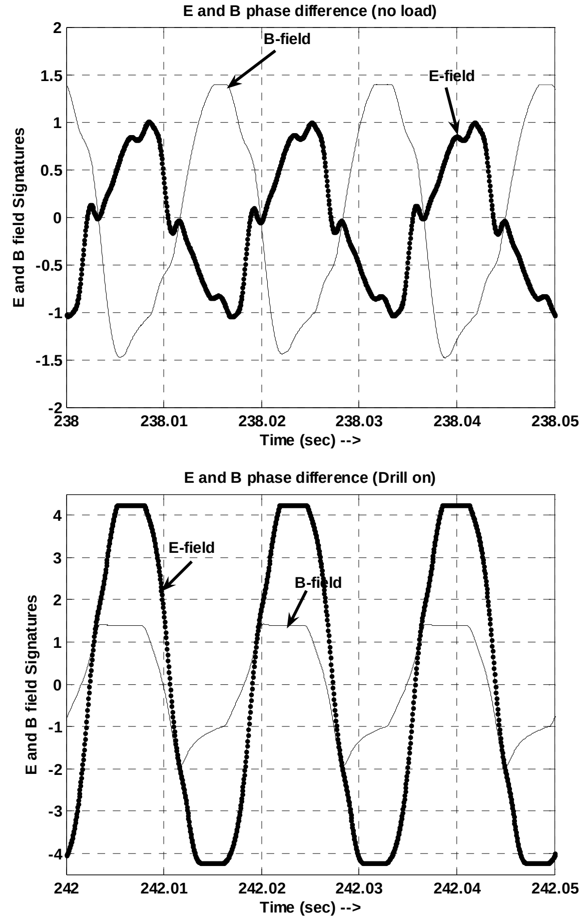


Figure 9 : Output of E and B-Field Sensors

can exploit the fact that man-made objects tend to be composed of canonical geometric shapes that have smooth edges and sharp corners. On the other hand, natural object tend to be rough and jagged.

We are currently developing algorithms to segment out man-made objects from a visible image by analyzing the contour of the objects. First, the image is segmented using techniques based on edges [7] and unified regions [8]. Then, the contour associated to each segment is analyzed. Specifically, features such as fractal dimension via box counting [14] and curvature [15] will be extracted. The features will be used to develop a Bayesian man-made object detector similar to how amplitude features are used in the human presence method of Section 4.

Let $H_{o,0}$ and $H_{o,1}$ represent the hypotheses that the $i$-th contour is natural and man-made, respectively. The set of features for the $i$-th contour is represented by the vector $\mathbf{f}_i$. Training data will be used to determine the likelihoods of the two hypotheses as

$$l_{o0}(\mathbf{f}_i) = p(\mathbf{f}_i \mid H_{o,0}), \quad l_{o1}(\mathbf{f}_i) = p(\mathbf{f}_i \mid H_{o,1}). \qquad (7)$$

The likelihoods may be modeled by Gaussians as in (2) or by other distributions if necessary. Similar to (5), the posterior probability for $H_{o,1}$ is computed as

$$p(H_{o1} \mid \mathbf{f}_i) = \frac{l_{o1}(\mathbf{f}_i)\, p(H_{o,1})}{l_{o1}(\mathbf{f}_i)\, p(H_{o,1}) + l_{o0}(\mathbf{f}_i)\, p(H_{o,0})}. \qquad (8)$$

The man-made object that leads to the detected contour could be abandoned. It is crucial to determine if the contour represents a recently used object. When a man-made machine is used, heat will be generated at the friction points. This means that the object will radiate heat at concentrated location. On the other hand, if the object has been turned off for a long time, the only heat is created by solar loading, which tends to distribute the heat evenly over the object. Thus, the distribution of heat over an object contour can provide inference about recent human activity. Furthermore, the decay of the heat over time may indicate whether or not the heat source is man-made or natural.

The heat distribution over an object contour requires registration of the visible and infrared imagery. There are a number of difficulties in registering the outputs from these cameras due to their differences in focal length, field-of-views, lens characteristics, image resolution, as well as viewing aspect and height, We are developing algorithms to register images from visible and IR cameras based on geometric transformations and stereo techniques, see [9], [11], [12].

Once the images from IR and visible cameras are properly registered, we will use them to detect certain human activities. In the case of the machine shop scenario, we may detect recent human activities based on the thermal footprint of the drill press, even when the drill press has been idle for a period of time. Both spatial and temporal features describing the distribution of the heat may provide inference. For instance, we plan to derive spatial features **v** that represents the spread of the distribution over the interior of the contour, e.g., variance or entropy. We also plan to derive a temporal feature **t** that represents the "average" decay of heat as function of time over the interior of the contour.

Once the features are defined, the activity detector consists of the calculation of the posterior probability of the human activity hypothesis $H_{a1}$ over the entire scene given the activity and contour features for the entire scene. To this end, training data will be used to derive the likelihoods of the no activity $H_{a,0}$ and human activity $H_{a,1}$ hypotheses for each of the $N_c$ contours. The likelihoods associated to the $i$-th contour are derived only when the object under analysis is man-made so that the likelihoods are

$$\begin{aligned} l_{a1}(\mathbf{v}_i, \mathbf{t}_i) &= p(\mathbf{v}_i, \mathbf{t}_i \mid \boldsymbol{H}_{a1}, \boldsymbol{H}_{o1}), \\ l_{a0}(\mathbf{v}_i, \mathbf{t}_i) &= p(\mathbf{v}_i, \mathbf{t}_i \mid \boldsymbol{H}_{a0}, \boldsymbol{H}_{o1}). \end{aligned} \qquad (9)$$

Again, the likelihoods may be modeled as Gaussians or some other distribution if necessary. The likelihoods for the $i$-th contour conditioned on the contour features are simply the likelihoods defined in (9) multiplied by the posterior probability that the contour is man-made. The likelihoods that the entire scene does or does not contain evidence of human activity assume that the features for each contour are independent, conditioned on the activity hypothesis, i.e.,

$$\begin{aligned} l_{a1}(\boldsymbol{V},\boldsymbol{T} \mid \boldsymbol{F}) &= \prod_{i=1}^{N_c} l_{a1}(\mathbf{v}_i, \mathbf{t}_i)\, p(H_{o,1} \mid \mathbf{f}_i), \\ l_{a0}(\boldsymbol{V},\boldsymbol{T} \mid \boldsymbol{F}) &= \prod_{i=1}^{N_c} l_{a0}(\mathbf{v}_i, \mathbf{t}_i)\, p(H_{o,1} \mid \mathbf{f}_i), \end{aligned} \qquad (10)$$

where $N_c$ is the number of contours in the scene.

The human activity likelihood due to imagers will be combined with similar likelihoods computed from acoustic and seismic sensors. As in Section 4, the direct presence of humans will be obtained by spectral $\boldsymbol{S}$ and gait features $\boldsymbol{G}$ for acoustic and seismic sensors, respectively, and the likelihoods for the $H_{a0}$ and $H_{a1}$ hypotheses are derived by (1). Other features will be derived for the acoustic and seismic sensors to pick up 60Hz harmonics due to the machinery. Let's label these machinery features as $\boldsymbol{H}_a$ and $\boldsymbol{H}_s$ for the acoustic and seismic sensors respectively. Given that all sensor features are statistically independent when conditioned on either hypotheses, then the likelihoods for the two hypotheses using all features is

$$\begin{aligned} l_{a1}(\boldsymbol{X}) &= l_{a1}(\boldsymbol{V},\boldsymbol{T} \mid \boldsymbol{F})\, l_{a1}(\boldsymbol{S})\, l_{a1}(\boldsymbol{H_a})\, l_{a1}(\boldsymbol{G})\, l_{a1}(\boldsymbol{H_s}), \\ l_{a0}(\boldsymbol{X}) &= l_{a0}(\boldsymbol{V},\boldsymbol{T} \mid \boldsymbol{F})\, l_{a0}(\boldsymbol{S})\, l_{a0}(\boldsymbol{H_a})\, l_{a0}(\boldsymbol{G})\, l_{a0}(\boldsymbol{H_s}), \end{aligned} \qquad (11)$$

where $\boldsymbol{X}$ is the concatenation of all the features. Finally, the posterior probability that the scene contains human activity is

$$p(H_{a1} \mid \boldsymbol{X}) = \frac{l_{a1}(\boldsymbol{X} \mid \boldsymbol{F})\, p(H_{a1})}{l_{a1}(\boldsymbol{X} \mid \boldsymbol{F})\, p(H_{a1}) + l_{a0}(\boldsymbol{X} \mid \boldsymbol{F})\, p(H_{a0})}. \qquad (12)$$

Figure 10 provides a flow graph to illustrate the multi-sensor processing to calculate the posterior probability given in (12). The detector declares the existence of human activity if the posterior probability in (12) exceeds a threshold. Future work will develop the modules in Figure 10, and evaluate the receiving operating characteristic (ROC) curves associated to the corresponding detector.

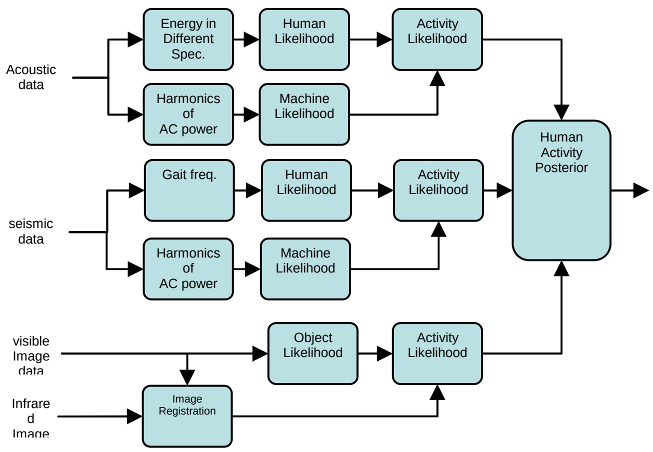


Figure 10: Fusion for human activity detection

# 6 Conclusion

We presented schemes to directly detect the presence of a human or to detect human activity and infrastructure. Both schemes take advantage of multiple sensor modalities through the use of Bayesian fusion. Experimental results demonstrate the utility of the fusion for human presence detection. The method can be further improved by incorporating video data and accumulating evidence temporally. Future work will center around the development of the modules consisting of the human activity detection scheme and enhancing the human presence detection scheme. Once both schemes are fully developed, they can be used to determine the threat level that exists in urban terrains, tunnels, caves and other remote sites.

# References

[1] T. Raju Damarla, et. all, “Personnel detection algorithm for disposable sensors using multi sensor data,” *Proc. MSS Battlefield Acoustic & Magnetic Sensing Symposium*, Laurel, Maryland, 2005.

[2] K. M. Houston and D. P. McGaffigan, “Spectrum Analysis Techniques for Personnel Detection Using Seismic Sensors”, *Proc. of SPIE*, Vol. 5090, 2003, pp. 162-173.

[3] J. M. Cathcart, “Phenomenological investigations into personnel signatures,” *Proc. of the SPIE*, Vol. 5796, pp. 428-434, May 2005.

[4] B. Mauro & J. M. Cathcart, “Analysis of visible band sensors for personnel detection”, *Proc. of SPIE*, Vol. 6231, 2006, pp. 62310D-1 - 62310D-12.

[5] Alan Edelstein, Jeff Dammann, and Pat Riordan,“ "Locating IEDs Using Magnetic Sensors & Tracking Algorithm Using a Single Vector Magnetometer”, *Proc. MSS Battlefield Acoustic & Magnetic Sensing Symposium*, Laurel, Aug. 2005.

[6] D. L. Hall and J. Llinas, *Handbook of Multisensor Data Fusion*, CRC Press: Boca Raton, FL, 2001.

[7] W. Ma and B. S. Manjunath, “Edge Flow: A Technique for Boundary Detection and Image Segmentation,” *IEEE Trans. Image Processing*, vol. 9, no. 8, pp. 1375-1388, Aug. 2000.

[8] J. F. Haddan and J. F. Boyce, “Image Segmentation by Unifying Region and Boundary Information,” *IEEE Trans. Pattern Analysis Machine Intelligence*, vol. 12, no. 10, pp. 929-948, Oct. 1990.

[9] L. G. Brown, “A Survey of Image Registration Techniques,” *ACM Computing Surveys*, vol. 24, no. 4, pp. 325-376, Dec. 1992.

[10] Bobby ***S.*** Rao and Hugh Durrant-Whyte, “A Decentralized Bayesian Algorithm for Identification of Tracked Targets”, *IEEE Transactions on Systems, Man, and Cybernetics*, VOL. 23, No. *6*. November/December 1993, pp. 1683-1698.

[11] M. Irani and P. Anandan “A unified approach to moving object detection in 2D and 3D scenes,” *IEEE Trans. on Pattern Analysis and Machine Intelligence*, vol. 20, no. 6, pp. 577-589, Jun. 1998.

[12] M Irani, B. Rousso, and S. Peleg, “Recovery of ego-motion using regional alignment,” *IEEE Trans. on Pattern Analysis and Machine Intelligence*, vol. 19, no. 3, pp. 268-272, Mar. 1997.

[13] M. S. Nixon, R. Chellappa, and T. Tan, *Human Identification Based on Gait*, Springer: New York, 2006.

[14] B. B. Mandelbrot, The Fractal Geometry of Nature, San Francisco: Freeman, 1982.

[15] F. Mokhtarian, “Silhouette-Based Isolated Object Recognition through Curvature Scale Space,” *IEEE Trans. on Pattern Analysis and Machine Intelligence*, Vol. 17, no. 5, pp. 539-544, May 1995.